# Neuro-Fuzzy Based Clustering Approach for Content Based Image Retrieval Using 2D-Wavelet Transform

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***Abstract*—In this paper we introduce neuro-fuzzy based clustering approach for content based image retrieval using 2D-wavelet transform(2D-DWT). Most of the image retrieval systems are still incapable of providing retrieval result with high retrieval accuracy and less computational complexity.To address this problem, we developed neural network -fuzzy logic cluster based approach for content based image retrieval using 2D-wavelet transform. The system performance improved by the learning and searching capability of the neural network combined with the fuzzy interpretation. This overcomes the vagueness and inconsistency due to human subjectivity. Multiresolution analysis using 2D-DWT can decompose the image into components at different scales, so that the coarest scale components carry the global approximation information while the finer scale components contain the detailed information. The empirical results show that the precision improved from 78% to 98% and average recall rate of 77% to 98% for the general purpose database size of 10000 images compared with other existing approaches.**

***Index Terms*—Color and texture based image retrieval, clustering, 2D Wavelet transform, Neural network and Fuzzy logic**

## I. INTRODUCTION

With the explosive growth in image records and the rapid increase of computer, retrieving images from a large-scale image database becomes one of the most active research fields. To give all images text annotations manually is tedious and impractical and to automatically annotate an image is beyond current technology. Content-based image retrieval (CBIR) is a technique to retrieve images semantically relevant to the user's query from an image database. In content based approach, users provide the system with image examples to retrieve the images. It is based on automatically extracted visual features from an image such as color, texture, and shape. Despite tremendous improvement in content based retrieval,it still have many limitations. First, it is difficult for the users to specify the visual queries with the low level features. Second, low level image features cannot precisely describe user information needs .However the gap between these low-level features and high level semantic meanings usually leads to poor performance.[1][11]. The process of grouping a set of objects or patterns into classes of similar objects is called clustering. Clustering is a process that organizes a data set into a number of groups (clusters) such that patterns within a cluster are more similar to each other than patterns belonging to different clusters. In other words, clustering is an important technique for discovering the inherent structure in any given pattern set. It has been applied across many disciplines including engineering, statistics, psychology, sociology, astronomy, biology, business, medicine to name a few [10][16]. There exists two categories for clustering task: hard and soft clustering. In hard clustering, each data object is assigned to exactly one cluster, while soft clustering is more desirable to let a data object be assigned several clusters partially. Hence, the soft clustering is also called neuro-fuzzy clustering [20][21]. Our goal of this paper is to provide methodology that concentrates on retrieving of images, defined by variety of clusters, in order to find the particular clusters.In this approach we integrated color-texture based image retrieval method with use of neuro-fuzzy system. From the initial returned images, users can select different clusters and retrieve from the database.

Most of early CBIR systems perform retrieval based primarily on global features ,including IBM'S QBIC[22] and MIT'S Photobook[23].It is common that users accessing a CBIR system look for objects.Thus,the aforementioned systems are likely to fail, since a single feature computed for entire image content cannot sufficiently capture the important properties of the individual images. In this paper, we present neuro-fuzzy clustering technique to retrieve the images as clusters with human visual perception. The rest of the paper is organized as follows: Section II presents the previous related works in the area of fuzzy and neural network based image retrieval. Section III presents architecture developed to facilitate the proposed approach and the IV section we describe the color and V section texture feature based retrieval. Section VI experimental results and we presented conclusion in section VII.

## II .RELATED WORK

Fagin[24] and Ortega et al [25] are pioneers who integrated fuzzy logic models into CBIR systems .They proposed algorithms to evaluate the fuzzy query, and showed the effectiveness through proven theorems and experimental results. Medasani and krishnapuram [14] proposed a fuzzy-based linguistic query in their CBIR system. Their membership query is formulated by a Gaussian mixture membership function and fuzzy

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connectives. It provides natural and friendly interface to their system. Dubois et al [13] illustrated a fuzzy logic framework for a query by example scheme, where the users can give relevant or irrelevant examples together with their significance. Their framework shows the feasibility of using fuzzy-based relevance feedback in CBIR systems. Lin et al [26] designed a fuzzy logic CBIR system for finding textures. Their system provides users with linguistic and visual queries which are formulated by fuzzy triangular membership functions. The Lin's system also incorporates relevance feedback to improve the retrieval accuracy through iteratively modifying membership functions. Their fuzzy-based framework is simple, intuitive and effective in texture retrieval. It is worth mentioning that Lin's system as well as other fuzzy logic CBIR systems, does not retain each user's preference during retrieval, thus retrieval accuracy is impaired. Chih-Yi Chiu et al[12]framework is proposed to alleviate two problems in traditional CBIR systems, including the semantic gap and the perception subjectivity. Kulkarni et al [6],[17],[18] proposed a neuro – fuzzy technique for CBIR.It is based on fuzzy interpretation of natural language, neural network learning and searching algorithms. Our proposed system based on neuro-fuzzy clustering with multiresolution analysis using wavelet transform capable of achieving better precision, average recall rate and classification rate.

## III. PROPOSED ARCHITECTURE

The architecture developed to facilitate color and texture based searching is illustrated schematically in Fig.2.The query processing and image matching is the main contribution of the architecture. Features of images such as color and texture are extracted from image and stored in the database. The query image is processed to compute color features as in section IV. The same query image is given as input image for texture based retrieval, the 2D-DWT is applied to query image, texture features of the query image and database image is stored in the database. Our proposed work takes the advantage of the membership degree to each feature, fuzzifying the neural net works output by means of membership function. The query to retrieve the images from database is prepared in terms of natural language such as mostly content, many content and few content of the some specific color. Fuzzy logic is used to define the query. We define nine colors that fall within the range of human perception.The feature representation set of colors and texture is {red, green, blue, white, black, yellow, orange, pink, purple,energy}.These ten colors have been used as input to the neural network and produces content type as output. *Mostly, many*, and *few* indicate the output. Accordingly the related similarity measure should proximity between two vectors, independently described by their respective features.

Color is the most popularly used features in image retrieval and indexing. On the other hand, due to its inherent nature of inaccuracy in description of the same semantic content by different color quantization and /or by the uncertainty of human perception, it is important to capture this inaccuracy when defining the features. We apply fuzzy logic to the traditional color histogram to help capture this uncertainty in color indexing [2][5].

We assume that any color is a fuzzy set. That means we will associate any color to a fuzzy functions, $\mu_C: \mu \to [0,1]$ and for any color $c'$ of the universe, $\mu_C(c')$ is the resemblance degree of the color $c'$ to the color $c$. The fuzzy model we define should follow the property that the resemblance degree decreases as inter-color distance increases. So we assume the particular color content for each image to *mostly, many* and *few*. In our model, the interpretation ranges of the values used are [0.9,1] for *mostly*,[0.4,0.5] for *many* and [0.15,0.25] for *few*[9][11]-[14].

### A .Semantic rule M

M is the semantic rule mapping from low-level feature U to the high level fuzzy semantics of T, that is to say, for $u \in U, t \in T(x)$. It assumes a value in [0,1] called degree of membership to $u$ according to the linguistic value $t$. We can formally describe the task as sample set $\{(V_1' y_1) \dots (V_n' y_n)\}$, in which $V_i' \in U (i = 1, \dots n)$ represents color histogram and $y_i (i = 1 \dots n)$ is the degree of membership.[17]Neural network is used as an adaptive retrieval system which incorporates learning capability into the network module where the network weights represent adaptability. This learning approach has several advantages over traditional retrieval approaches. It allows the retrieval system to solve the problem of fuzzy understanding of users' goals [7][15]-[17]

We have adopted a Self-Organizing Tree Map (SOTM) and a Learning Vector Quantization (LVQ) which together were used to form a local data clustering [9][15]. The SOTM works well for the combined color-texture features for the construction of unsupervised suitable clustering algorithm. It is more effective than the K-means and the self organizing feature map (SOM) algorithm particularly when the input space is high dimensionality. Thus, SOTM is chosen in our work to locate cluster centers in the high dimensional space of image features. To carry out SOTM/LVQ algorithms, we have given a set of training samples corresponding to retrieved images from a previous search operation [15].This is used for approximating the distribution of the relevant samples which are associated with the training data and incorporated into radial basis function (RBF) network for ranking of an image database [29].

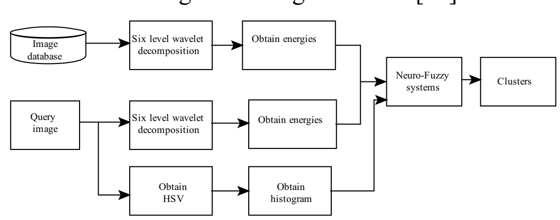


Figure.1 Proposed architecture




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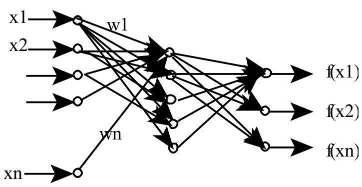


Figure.2. Architecture of the RBF netwok

We denote this training data with two sets of vectors. Positive sample set(relevant images) $X^+ = \{x_1, ... x_N\} \subset R^p$,and negative sample set(non-relevant images) $X^- = \{x'_1, ... x'_M\} \subset R^p$.We assign each input vector in $X^+$ into an SOTM algorithm to create the weight vectors, where as the vectors in $X^-$ are used in the LQV algorithm for further adjustment of the weight vectors. SOTM algorithm is given as follows.[15]

Step 1. *Initialization*. Choose the root nodes $\{w_j\}_{j=1}^{l}$ from the available set of input vectors $\{x_i\}_{i=1}^{N}$ in a random manner.

Step 2. *Similarity matching*. Randomly select a new data point $x$,and find the best matching neuron at time step $t$ by using the minimum-distance Eudlidean criterion:

$$w_j^* = \Sigma_j^* \|x(t) - w_j\|, j = 1,2 \ldots l \quad (1)$$

Step 3. *Updating*. If $\|x(t) - w_j\| \leq H(t)$,where $H(t)$ is the hierarchy function used to control the levels of tree, then assign $x(t)$ to the jth cluster,and adjust the synaptic weight vector according to the reinforced learning rule:

$$w_j(t+1) = w_j(t) + \alpha(t)|x(t) - w_j(t)|, \quad (2)$$

Where $\alpha(t)$is the learning rate, which decreases monotonically with time,$0 < \alpha(t) < 1$. Else form a new subnode starting with $x$.

Step 4. *Continuation*. Continue with step 2 until no changes in the feature map.

The SOTM algorithm obtains a new set of cluster centres $V_0 = \{v_1, ... v_k ... v_K\}$,where the number of centres $K$ is controlled by the the function $H(t)$.In the experiment,$H(t)$ was initialized by the norm of the training vectors in $X^+$,and was reduced linearly.

Step 5. *Cluster Modification* .At this stage, the negative samples in $X^-$are used to tune the decision boundaries of the initial set $V_0$.We employ the antireinforced learning rule in the LVQ algorithm to perform this operation. The algorithm starts with randomly choosing input vector $x'_m(t)$ from the training set $\{x'_m\}_{m=1}^{M}$. Then, classify $x'_m(t)$ to the node $v_i$ if

$$\|x'_m(t) - v_i\| < \|x'_m(t) - v_k\|, \forall k \neq i, \quad (3)$$

apply the antireinforced learning rule to the corresponding cluster centers as

$$v_i(t+1) = v_i(t) - \eta(t)[x'_m(t) - v_i(t)] \quad (4)$$

Where $\eta(t)$ is the learning constant which decreases monotonically with the number of iterations $t$, $0 \leq \eta(t) \leq 1$.After several training data, the node vectors converge and the cluster modification process is complete.

We assign each input vector $v_m$ as centre of the corresponding Gaussian kernel in the network.For the arbitrary input vector x,the output of the *m*th RBF unit is given by

$$G_m(X, V_m, \sigma_m) = \exp\left(-\frac{(X-V_m)^T(X-V_m)}{2\sigma_m^2}\right) \quad (5)$$

Where $\sigma_m$ is a smoothing parameter defined as

$$\sigma_m = \delta \min\|V_m - V_i\|, \; i=1,2....M \quad (6)$$

with $\delta$=0.5 being an overlapping factor.The estimated function output *f(*x*)*for x is then given as

$$f(x) = \sum_{m=1}^{M} G_m(X, V_m, \sigma_m) \quad (7)$$

TABLE I

NEURAL NETWORK PARAMETERS FOR EXPERIMENTS

| Inputs | Outputs | Hidden Units | Training Pairs | $\eta$ | $\alpha$ | Iterations |
|---|---|---|---|---|---|---|
| 10 | 3 | 5 | 307 | 0.7 | 0.2 | 50 |

## IV. COLOR FEATURE BASED RETRIEVAL

Image retrieval systems have implemented one or more color features, for example, dominant colors, color moments, color sets, color coherence vector, color correlogram and autocorrlogram. The good color space for image retrieval system should preserve the perceived color differences. In other words, the numerical Euclidean difference should approximate the human perceived difference[5]

### *1. Color Conversion*

In order to use a good color space for a specific application, color conversion is needed between color spaces.Red,Green,Blue (RGB),Hue Saturation Value (HSV).

### *A.RGB to HSV Conversion*

In Fig.3 Obtainable HSV colors lie within a triangle whose vertices are defined by the three primary colors in RGB space[1]

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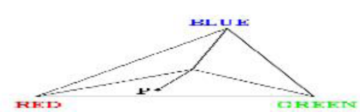


Figure.3.RGB to HSV Conversion

The hue of the point P is the measured angle between the line connecting P to the triangle centre and line connecting RED point to the triangle centre.

The saturation of the point P is the distance between P and triangle centre. The value (intensity) of the point P is represented as height on a line perpendicular to the triangle and passing through its centre. The greyscale points are situated into the same line and the conversion formula is as follows

$$H = Cos^{-1}\left\{\frac{\frac{1}{2}[(R-G)+(R-B)]}{\sqrt{(R-G)^2+(R-B)(G-B)}}\right\} \quad (8)$$

$$S = 1 - \frac{3}{R+G+B}[\min(R,G,B)] \quad (9)$$




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$$V = \frac{1}{3}(R + G + B) \quad (10)$$

*B. HSV to RGB Conversion*

Conversion from HSV space to RGB space is more complex and given to the nature of the hue information, we will have a different formula for each sector of the color triangle.[1]

Red-Green sector for $0^o < H \le 120^o$

$$r = \frac{1}{3}\left|1 + \frac{S\cos H}{\cos(60 - H)}\right| \quad (11)$$

$$b = \frac{1}{3}(1 - s) \quad (12)$$

$$g = 1 - (r + b) \quad (13)$$

Green-Blue sector for $120^0 < H \le 240^0$

$$r = \frac{1}{3}(1 - s) \quad (14)$$

$$g = \frac{1}{3}\left|1 + \frac{S\cos H}{\cos(60 - H)}\right| \quad (15)$$

$$b = 1 - (r + b) \quad (16)$$

Blue-Red sector for $240^o < H \le 360^o$

$$r = 1 - (r + b) \quad (17)$$

$$g = \frac{1}{3}(1 - s) \quad (18)$$

$$b = \frac{1}{3}\left|1 + \frac{S\cos H}{\cos(60 - H)}\right| \quad (19)$$

V. TEXTURE BASED IMAGE RETRIEVAL

Texture is another important property of images. Various texture representations have been investigated in pattern recognition and computer vision. Basically, texture representation methods can be classified into two categories: structural and statistical. Structural methods, including morphological operator and adjacency graph, describe texture by identifying structural primitives and their placement rules. They tend to be most effective when applied to textures that are very regular. Statistical methods, including Fourier power spectra, co-occurrence matrices, shift-invariant principal component analysis(SPCA),Tamura feature[28], wold decomposition, Markov random field, fractal model, and multiresolution filtering techniques such as Gabor[26] and wavelet transform[3],[27],[28].

Since image is typically a two dimensional signal, a 2D equivalent of the DWT is performed. This is achieved by first applying the L and H filters to the lines of samples, row by row, then refiltering the output to the columns by the same filters. As the result, the image shown in Fig.3 is divided into 4 subbands, LL, LH, HL and HH as depicted in Fig.4. The LL sub band contains the low pass information of horizontal, vertical and diagonal orientation. The LL sub band provides a half sized version of input image which can be transformed again to have more levels of resolution.Generally, an image is partitioned into L resolution levels by applying the 2D DWT (L-1) times[3],[27]

By wavelet transform, we mean the decomposition of an image with family of real orthogonal bases $\psi_{mn}(x)$ obtained through translation and dilation of a kernel function $\psi(x)$ known as mother wavelet

$$\psi_{mn}(x) = 2^{\frac{-m}{2}}\psi(2^{-m}x - n) \quad (20)$$

Where $m$ and $n$ are integers.Due to the orthonormal property,the wavelet coefficients of a signal $f(x)$ can be easily computed via

$$c_{mn} = \int_{-\infty}^{+\infty} f(x)\psi_{mn}(x)dx \quad (21)$$

and the synthesis formula

$$f(x) = \sum_{mn} c_{mn}\psi_{mn}(x) \quad (22)$$

can be used to recover $f(x)$ from its wavelet coefficients


Fig.4.Orginal image


Fig.5.One level decomposition

To construct the mother wavelet $\psi(x)$, we may first determine a scaling function $\phi(x)$,which satisfies the two-scale difference equation

$$\phi(x) = \sqrt{2}\sum_k h(k)\phi(2x - k) \quad (23)$$

Then the wavelet kernel $\psi(x)$ is related to the scaling function via

$$\psi(x) = \sqrt{2}\sum_k g(k)\phi(2x - k) \quad (24)$$

where

$$g(k) = (-1)^k h(1 - k) \quad (25)$$

The coefficients $h(k)$ in (23) have to several conditions for the set of basis wavelet functions in (21) to be unique, orthonormal, and have a certain degree of regularity.

The coefficients $h(k)$ and $g(k)$ play a very crucial role in a given discrete wavelet transform.To perform the wavelet transform does not require the explicit forms of $\phi(x)$and $\psi(x)$ but only depends on $\boldsymbol{h(k)}$andg(k). Consider a J-level wavelet decomposition which can be written as

$$f_0(x) = \sum_k c_{0,k}\phi_{0,k}(x)$$
$$= \sum_k \left(c_{J+1,k}\phi_{J+1,k}(x) + \sum_{j=0}^{J} c'_{j+1,k}\psi_{j+1,k}(x)\right) \quad (26)$$

Where coefficients $c_{0k}$ are given and coefficients $c_{j+1n}$ and $c'_{j+1n}$ at scale $j+1$ are related to the coefficients $c_{jk}$ at scale $j$ via

$$c_{j+1n} = \sum_k c_{jk}h(k - 2n) \quad (27)$$

$$c'_{j+1n} = \sum_k c_{jk}g(k - 2n) \quad (28)$$

Where $0 \le j \le J$.Thus,(27) and (28) provides a recursive algorithm for wavelet decomposition through $h(k)$ and $g(k)$,and the coefficients $c_{Jn}$ for a low resolution component $\phi_{Jk}(x)$.By using a similar approach,we can derive a recursive algorithm for function synthesis based on its wavelet coefficients $c'_{jn}$ $0 \le j \le J$ and $c_{Jn}$

$$c_{jk} = \sum_n c_{j+1n}h(k - 2n) + \sum_n c'_{j+1n}g(k - 2n) \quad (29)$$

It is convenient to view the decomposition (8) as passing a signal $c_{jk}$ through a pair of filters $H$ and $G$ with impulse responses $\tilde{h}(n)$ and $\tilde{g}(n)$ and down sampling the filtered signals by two (dropping every other sample), where $\tilde{h}(n)$ and $\tilde{g}(n)$ are defined as




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$\tilde{h}(n) = h(-n), \tilde{g}(n) = g(-n)$.

The pair of filters *H* and *G* correspond to the half band low pass and high pass filters respectively, and are called the quadrature mirror filters in the signal processing literature [5]

The reconstruction procedure is implemented by up sampling the sub signals $c_{j+1n}$ and $c^{l}_{j+1n}$ and filtering with $h(n)$ and $g(n)$,respectively, and adding these two filtered signals together.Usually the signal decomposition scheme is performed recursively to the output of lowpass filter $\tilde{h}(n)$.

The wavelet packet basis functions $\{W_n'\}_{n=0}^{\infty}$ can be generated from a given function $W_0'$ as follows

$$W_{2n}'(x) = \sqrt{2}\sum_k h(k) W_n'(2x-k) \quad (30)$$

$$W_{2n+1}'(x) = \sqrt{2}\sum_k g(k) W_n'(2x-k) \quad (31)$$

Where the function $W_0'(x)$ can be identified with the scaling function $\phi$ and $W_1'$ with the mother wavelet $\psi$.Then,the wavelet packet bases can be defined to be the collection of orthonormal bases composed of functions of the form $W_n'(2^l x - k)$,where *l, k* $\in Z, n \in N$. Each element is determined by a subset of the indices: a scaling parameter *l,* a localization parameter *k,* and an oscillation parameter *n*.

The 2D wavelet (or wavelet packet) basis functions can be expressed by tensor product of two 1-D wavelet (or wavelet packet) basis functions along the horizontal and vertical directions. The corresponding 2-D filter coefficients can be expressed as

$$h_{LL}(k,l) = h(k)h(l), h_{LH}(k,l) = h(k)g(l), \quad (32)$$

$$h_{HL}(k,l) = g(k)h(l), h_{HH}(k,l) = g(k)g(l) \quad (33)$$

Where the first and second subscripts in (33) and (34) denotes the low pass and highpass filtering characteristics in the $x$-and $y$-directions respectively[3].

## VI.RESULTS AND DISCUSSION

To evaluate the performance of our image retrieval clustering algorithm, the proposed framework is tested with a general-purpose image database of about 10000 images each size 256×256 approximately 1000 categories from COREL. In our system we have selected categories such as roses, buses, elephants, lions, and sunflowers etc. The system supports both image retrieval as well as clustering. For each experiment we first selected one image as a query image randomly from the database and then obtained the retrieved images. Then we selected one or more images as clusters from the retrieved images. The selected images (clusters) were used as query images for next step to retrieve the particular clusters. The wide range of queries which could be submitted as a result of different query images also possible. The simulation results of the image retrieval is shown in Fig.6.Retrieval of Clusters 1 shown in Fig.7, Retrieval of Clusters 2 shown in Fig.8, Retrieval of Clusters 3 shown in Fig.9, Retrieval of Clusters 4 shown in Fig.10. Retrieval of Clusters 5 shown in Fig.11.Our system has been tested with the average recall rate (AVRR), and precision measures[1]used the database with 10000 real world images

$$\text{Precision} = \frac{A \cap B}{A} \quad (31)$$

$$\text{AVRR} = \frac{A \cap B}{B} \quad (32)$$

A=Number of retrieved images,

B=Number of relevant images


Figure.6.Genreral CBIR retrieval.

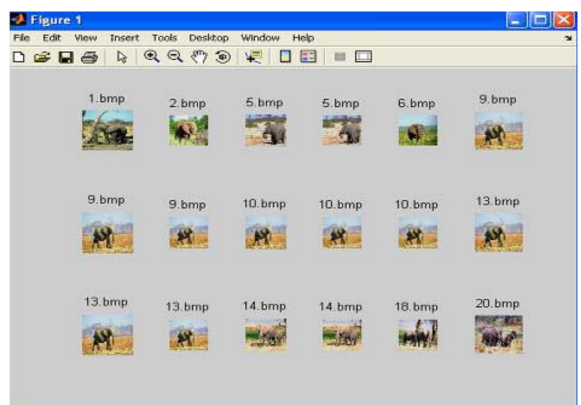


Figure.7.Cluster1 retrieval.

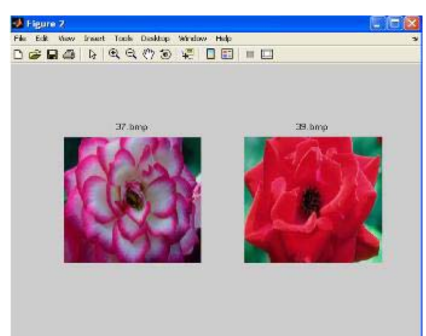


Figure.8 Cluster 2 retrieval.




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Figure.9 Cluster 3retrieval.

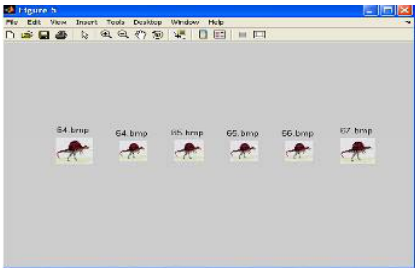

Figure.10. Cluster 4 retrieval.

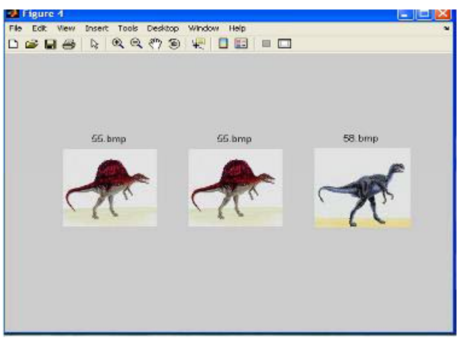


Figure.11 Cluster 5 retrieval.

TABLE II
PRECISION FOR VARIOUS APPROACHES

| Approach | Average recall rate | | | | |
|---|---|---|---|---|---|
| | Number of query images | | | | |
| | 1 | 2 | 3 | 4 | 5 |
| NN | 0.7713 | 0.772 | 0.773 | 0.7743 | 0.7855 |
| RFM | 0.6910 | 0. 699 | 0.698 | 0.6994 | 0.6992 |
| Fuzzy | 0.7874 | 0.780 | 0.772 | 0.7812 | 0.7886 |
| Proposed | 0.98 | 0.98 | 0.98 | 0.98 | 0.98 |

Table II provides a detailed comparison of precision obtained for the top five queries considered using NN,RFM,Fuzzy and proposed approach. Precision performance improved upto 21% compared to NN and upto24% compared to RFM and upto 20% compared to Fuzzy approach on query image no.1.and almost precision for all other query images. For the top five queries computed and tabulated in Table.II and other 10 query images shown in Fig.12.

TABLE III
AVERAGE RECALL RATE FOR VARIOUS APPROACHES

| Approach | Precision | | | | |
|---|---|---|---|---|---|
| | Number of query images | | | | |
| | 1 | 2 | 3 | 4 | 5 |
| NN | 0.763 | 0.764 | 0.7636 | 0.7635 | 0.7655 |
| RFM | 0.711 | 0. 729 | 0.7286 | 0.7294 | 0.7292 |
| Fuzzy | 0.719 | 0.718 | 0.7125 | 0.7125 | 0.1189 |
| Proposed | 0.98 | 0.98 | 0.98 | 0.98 | 0.98 |

Table III provides a detailed comparison of Average recall rate obtained for the top five queries considered using NN,RFM,Fuzzy and proposed approach. Precision performance improved upto 22% compared to NN and upto27% compared to RFM and upto 27% compared to Fuzzy approach on query image no.1.and almost precision for all other query images. For the top five queries computed and tabulated in Table.III and other 10 query images shown in Fig.13.

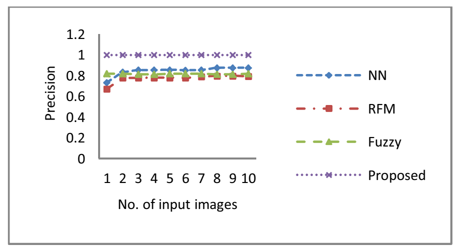


Figure. 12 Precision for 10 different query images

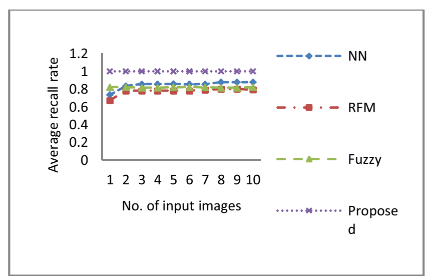


Figure. 13Average recall rate for 10 different query images

## VI. CONCLUSION

For the sake of alleviating the semantic and perception subjectivity problems, a CBIR system should well characteristize a mapping from image features to human concepts, and effectively captures the user's preference on retrieval by means of clustering. The neuro-fuzzy system with clustering can provide a flexible mapping from low level features to high level human concepts. The main contribution of this works is in building various features required by a working system for efficient and effective retrieval of images. This proposed approach greatly reduces user's effort and captures the user's information needed more precisely. Furthermore,the effectiveness of the proposed approach have been validated by a large number of experiments. Our




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proposed approach improves the precision from 79% to 98 %, compared with NN approach,71% to 98% compared with RFM approach and 78% to 98% compared with Fuzzy approach .And almost high same average recall rate compared with NN approach, RFM approach and Fuzzy approach. Also our proposed approach retrieves the images as clusters with high human visual perception and more classification rate.

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